A Practical Guide to Learning Analytics

Wisconsin Programs Using Data to Improve Learning

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WIsconsin
Digital Learning Collaborative
Innovate. Collaborate. Educate.

About Wisconsin Digital Learning Collaborative

The Wisconsin Digital Learning Collaborative (WDLC) is a unique statewide partnership with a mission to “provide equitable access to high-quality online and blended learning resources throughout Wisconsin.” This partnership results in every student in any school district having access to quality online and blended learning offerings. It also provides digital learning resources for teachers to use in their classrooms. Access to online courses, technology, and resources are available to districts through the WDLC regardless of size, geography, or learning model.

The WDLC consists of three collaborating organizations. The Wisconsin Virtual School (WVS) provides supplemental online courses, as well as, services to support the planning and implementing of digital initiatives to a large majority (200+) of the school districts across Wisconsin. The Wisconsin eSchool Network (WEN) is a consortium of 28 partners that provides access to online courses, technology, operational support, digital learning professional development, and other services to its members. Together, WEN and WVS form the foundation of the Collaborative. The third organization, the Department of Public Instruction (DPI), provides quality assurance and helps raise awareness of WDLC. It also provides some fiscal support through the segregated universal service fund administered by the Wisconsin DPI.

In addition to the WDLC representing the digital learning interests of all districts, it also leverages shared knowledge and best practices to reduce costs. It offers a wide variety of resources, services, and benefits that districts need in order to offer online and blended learning options to students.

See the end of this report for a full list of WDLC district and affiliate partners.

About the Virtual Learning Leadership Alliance

The WDLC is honored to partner with the Michigan Virtual Learning Research Institute as part of our collaborative partnership of the Virtual Learning Leadership Alliance (VLLA). With a commitment to quality the VLLA is an association of the chiefs of virtual programs that provides collegial support and collaborative opportunities to the individual members and member organizations to share resources, services, and expertise. This project is one of many collaborative projects related to the VLLA. The WDLC would like to thank the Michigan Virtual Learning Research Institute for our partnership in studying our partner practices across Wisconsin.

About Michigan Virtual Learning Research Institute

In 2012, the Governor and Michigan Legislature passed legislation requiring *Michigan Virtual™,* formally *Michigan Virtual University®*, to establish a research center for online learning and innovation. Known as *Michigan Virtual Learning Research Institute®* (*MVLRI®*), this center is a natural extension of the work of *Michigan Virtual*. Established in 1998, *Michigan Virtual's* mission is to advance K-12 digital learning and teaching through research, practice, and partnerships. Toward that end, the core strategies of *MVLRI* are:

- Research – Expand the K-12 online and blended learning knowledge base through high quality, high impact research;
- Policy – Inform local, state, and national public education policy strategies that reinforce and support online and blended learning opportunities for the K-12 community;
- Innovation – Experiment with new technologies and online learning models to foster expanded learning opportunities for K-12 students; and
- Networks – Develop human and web-based applications and infrastructures for sharing information and implementing K-12 online and blended learning best practices.

Michigan Virtual dedicates a small number of staff members to *MVLRI* projects as well as augments its capacity through a fellows program drawing from state and national experts in K-12 online learning from K-12 schooling, higher education, and private industry. These experts work alongside *Michigan Virtual* staff to provide research, evaluation, and development expertise and support.

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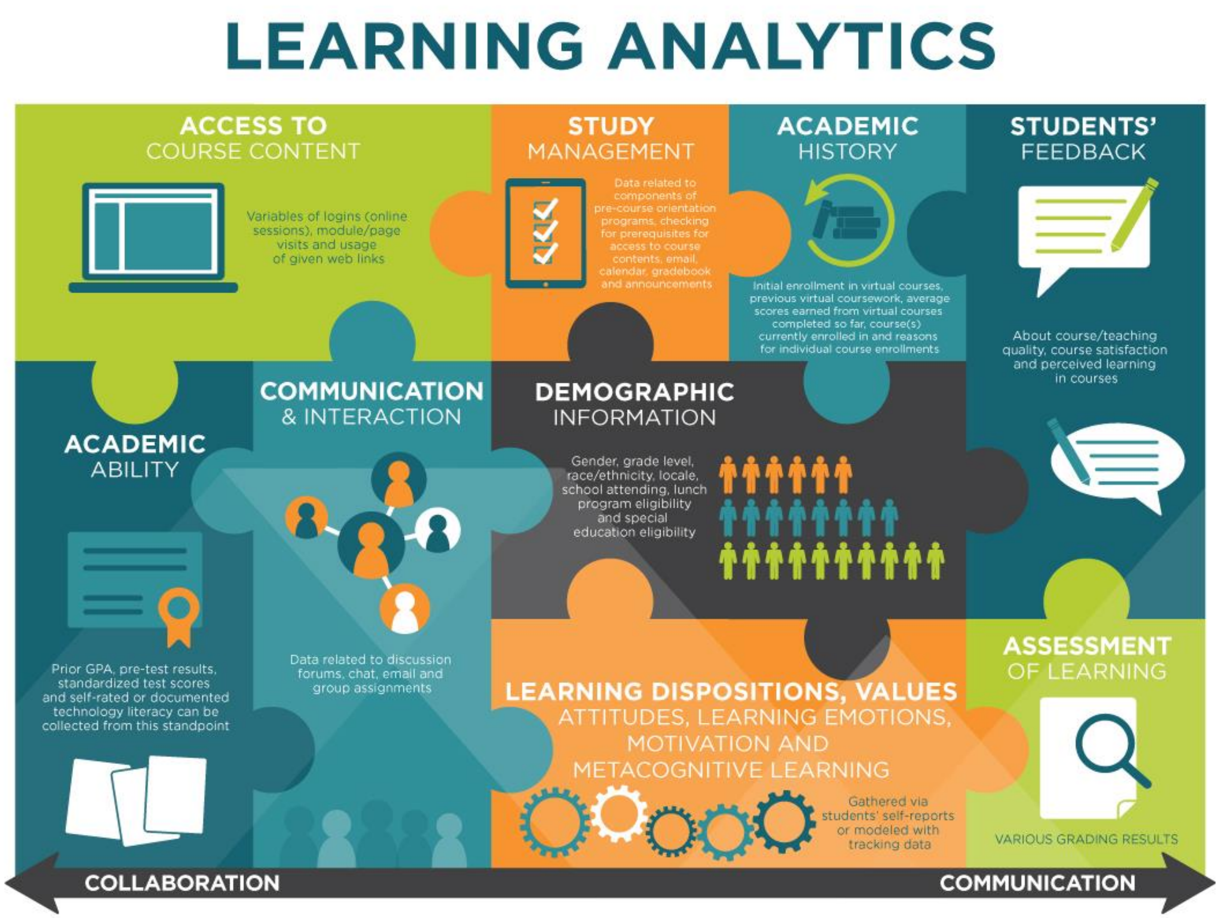
Introduction

Stakeholders of educational entities know about the importance of data-based decision making and the utility of learning analytics as a form of that decision making. However, they need information and knowledge about the practical application of such an infrastructure. Designing learning analytics involves various expertise and components; among those elements, understanding useful factors to include in analytic modeling is foundational. This report will center on the types of data to be collected and how they should be used to inform and enhance successful teaching and learning practices. The first part of the report outlines a variety of data on course activities and student characteristics that are indicators of later performance. The second part of the report presents exemplar studies using learning analytic approaches whereby the LMS data were explored in order to identify insights into patterns and degrees of student engagement, student learning strategies, study practices, and development of a learning community within the virtual classroom. This report also features examples of how two Wisconsin programs — Appleton Area School District's Appleton eSchool and Wisconsin Virtual School— use learning analytics to improve their processes. ." Before going into the rest of the report, below is an infographic that provides a visual representation of the content of this report.



Types of Data

Typical learning management system (LMS) data repositories gather and organize information on a wide array of learning behaviors. First, the data that provide useful insights into ***access to course content*** include variables of log-ins (online sessions), module/page visits, and usage of given Web links. Depending on the nature of the questions to be answered, these variables can be analyzed based on a variety of formats, including occurrence, degree, mode, or pattern.

The second dimension of learning behaviors is ***communication and interaction***. Data related to discussion forums, chat, email, and group assignments help us gain insights into students' engagement with and development of a learning community within the virtual classroom. In addition to degrees or patterns of occurrence of those indicators, contents of communication can be analyzed through data processing to categorize and, in turn, quantify them. The data associated with interactions can also be analyzed based on the agent, for instance, student-student, student-instructor, and student-other supporting agents (e.g., academic mentors).

Tracking variables such as assignments, group assignments, quizzes, self-assessment quizzes, and final grades highlights the dimension of ***assessment of learning***. The final grade is most often used as the learning outcome variable. Trajectories can be captured by those data on multiple measurement occasions. Data related to components of pre-course orientation programs, checking for prerequisites for access to course contents, as well as email, calendar, gradebook, and announcements could be aimed at informing the dimension of ***study management***.

The aforementioned data are a by-product of learner activities. In addition, learning analytics operate with data from users' self-reports. ***Students' feedback*** on course/teaching quality, course satisfaction, and perceived learning in courses are notable examples and help us gain insights that lead to greater understanding of courses, supportive services, and learners. The satisfaction degree can be modeled as the outcome variable, for instance, due to its predictive relationship with the student-to-instructor interactions. When the final grade is used as the outcome variable, student satisfaction, perceived learning, and/or student-reported program quality can be explored in terms of its direct or indirect impact on the learning outcome (i.e., mediation effects).

Often, analytics are designed to understand the predictive relationship between particular background information and learning processes and/or outcomes in courses. Also, a pure relationship between two variables could be targeted, while students' different backgrounds are controlled for, because the relationship between two variables may be distorted, for instance, an association between course activities and outcomes while confounding effects of students' different backgrounds are controlled for.

In this light, collecting valid and credible data on student background is critical. ***Demographic information*** includes gender, grade level, race/ethnicity, locale, school attending, lunch program eligibility, and special education eligibility. ***Academic ability*** is an important factor to be modeled or controlled for to avoid any confounding effects on outcomes; prior GPA, pre-test results, standardized test scores, and self-rated or documented technology literacy can be collected from this standpoint. Similarly, variables relevant to ***academic history*** are useful for modeling, including initial enrollment in virtual courses, previous virtual coursework, average scores earned from virtual courses completed so far, course(s) currently enrolled in, and reasons for individual course enrollments.

In an application of learning analytics, learner data focused on ***learning dispositions, values, attitudes, learning emotions, motivation, and metacognitive learning*** can be combined into the infrastructure. Learning analytics explore those affective, motivational, and dispositional aspects as learning processes and/or learning outcomes and enhance our understanding of students' capacity to take responsibility for their own learning and deeply engage with knowledge creation, rather than playing a passive role in sole knowledge transmission. This type of data is often gathered via users' self-reports by asking them to intentionally disclose what they say about themselves in terms of constructs such as: "changing/learning vs. being static," "critical curiosity vs. passivity," "meaning making vs. data accumulation," "resilience vs. dependence/fragility," "being rule-bound vs. creativity," "isolation or dependence vs. working interdependently," and "strategic awareness vs. being robotic."

When it comes to motivation and self-regulated learning, the Motivation and Self-Regulated Learning Questionnaire (MSLQ)[1] and Learning Study Strategies Inventory–High School Version (LASSI-HS)[2] are potential resources. The former was designed to gather information about students' self-efficacy, goal orientation, affective beliefs, cognitive and meta-cognitive strategy use, and self-regulation. The subscales of the latter include information processing, selecting main ideas, test strategies, attitude, motivation, anxiety, concentration, time management, self-testing, and study aids. However, neither instrument was sufficiently validated within the online/blended learning context.

The Online Self-Regulated Learning Questionnaire (OSLQ)[3] and Online Learning Self-Efficacy Scale (OLSES)[4] were validated with college students in the online/blended learning environment. The OSLQ captures student characteristics in terms of goal-setting, environment structuring, task strategies, time management, help-seeking, and self-evaluation, while the OLSES includes three subscales: learning in the online environment, time management, and technology use.

Rather than relying on self-reports, learning analytics could use LMS tracking variables in capturing student characteristics and consequent performance from the perspectives of motivation, meta-cognition, learning emotion, and/or dispositions. It is not easy to identify and operationally define indicators and, in turn, to obtain models that are representative of the

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[1] Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology*, *82*, 33.
[2] http://www.hhpublishing.com/_assessments/LASSI-HS/index.html
[3] Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S. L. (2009). Measuring self-regulation in online and blended learning environments. *The Internet and Higher Education*, *12*, 1-6.
[4] Whitney Alicia Zimmerman & Jonna M. Kulikowich (2016) Online Learning Self- Efficacy in Students With and Without Online Learning Experience, *American Journal of Distance Education*, 30, 180-191, DOI: 10.1080/08923647.2016.1193801

learning process from typical LMS trace data. However, if course contents contain special pedagogical components that reflect self-regulated learning or meta-cognition (e.g., tasks asking students to teach particular concepts and skills to a fictitious character), trace data such as frequency, patterns, timing, and sequence of studying events would model those constructs.

Finally, learning analytics can be performed not only at a personal level but also an institutional level. One can readily hypothesize the predictive relationship of variables of class size, instructor characteristics (role, education, quality, etc.), and the characteristics of on-site academic mentors.

Study Examples

The following section presents a detailed explanation of variables and analytic approaches exemplar studies employed in the K-12 online learning context.

Study Case 1	Liu and Cavanaugh (2011)
Reference	Liu, F., & Cavanaugh, C. (2011). High enrollment course success factors in virtual school: Factors influencing student academic achievement. *International Journal on E-Learning*, 10, 393-418.
Study Site Data Source	The data were collected during the 2007-2008 academic year from one state level virtual high school in the Midwestern US.
Variables	• Student information: Race/ethnicity, IEP status, enrollment status (part-time/full-time), and free or reduced lunch • Course behavior: The number of times student logged into the LMS, the time student stayed in the LMS, and teacher comments • Learning outcome: The final score in the course
Analytic Approach	Hierarchical linear modeling (HLM) to test the association between the learning outcome and course activity variables while student information covariates were accounted for.
Implication	The time students spent in the LMS was significantly associated with the final score in frequently enrolled-in subjects such as Algebra, Geometry, the second part of English 2, American History, and American Government.

Study Case 2	Stevens and Frazelle (2016)
Reference	Stevens, D., & Frazelle, S. (2016). *Online credit recovery: Enrollment and passing patterns in Montana Digital Academy courses* (REL 2016–139). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Northwest. Retrieved from https://ies.ed.gov/ncee/edlabs/regions/northwest/pdf/REL_2016139.pdf
Study Site Data Source	The study used 2013/14 data from the Montana Digital Academy (MTDA) online credit recovery program.
Variables	• Student information: Gender, grade level, and subject areas • Outcome: Course completion status (Fail/Pass)
Analytic Approach	Descriptive analysis was focused on distributions of enrollments and passing rates by the student information variables.

Implication	Study findings provide information about enrollment patterns and passing rates of MTDA's online credit recovery program to identify areas for additional investigation or improvement. For instance, the largest proportion of students enrolled in English courses, but the passing rate was lowest in mathematics courses.
Study Case 3	**Pazzaglia, Clements, Lavigne, & Stafford (2016)**
Reference	Pazzaglia, A. M., Clements, M., Lavigne, H. J., & Stafford, E. T. (2016). *An analysis of student engagement patterns and online course outcomes in Wisconsin* (REL 2016–147). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Midwest. Retrieved from http://ies.ed.gov/ncee/edlabs
Study Site Data Source	The study used WVS's LMS data for the 2014-15 academic year.
Variables	• Student information: Course type taken, gender, and grade level • Focus variable: The amount of time logged in to the course each week • Outcome: Course points earned and course activities completed in percentage
Analytic Approach	The primary approach was group-based trajectory modeling to identify data-driven sub-groups based on patterns of behavior across time. Those results were explored by group difference tests to compare characteristics across groups and to examine the association between group characteristics and course outcomes.
Implication	Understanding how students engage in online learning over time and how their engagement patterns are associated with learning outcomes is a good starting point when stakeholders seek ways to support student success. This study found six engagement patterns best represented by the model, in five of which students earned course points high enough to pass the course by showing patterns of consistently investing 2 hours per week or at least 1.5 hours per week.
Study Case 4	**DeBruler and Bae (2016)**
Reference	DeBruler, K. & Bae, J. (2016). *Educating students across locales: Understanding enrollment and performance across virtual schools*. Lansing, MI: Michigan Virtual University. Retrieved from http://media.mivu.org/institute/pdf/locale.pdf
Study Site Data Source	Various state virtual schools provided data for the research team.
Variables	• Student information: locale codes developed by the National Center for Education Statistics (NCES), including City, Suburb, Town, and Rural. If provided, variables of NCES SCED subject area, race/ethnicity, and gender were included. • Outcome: Course completion status (Fail/Pass)

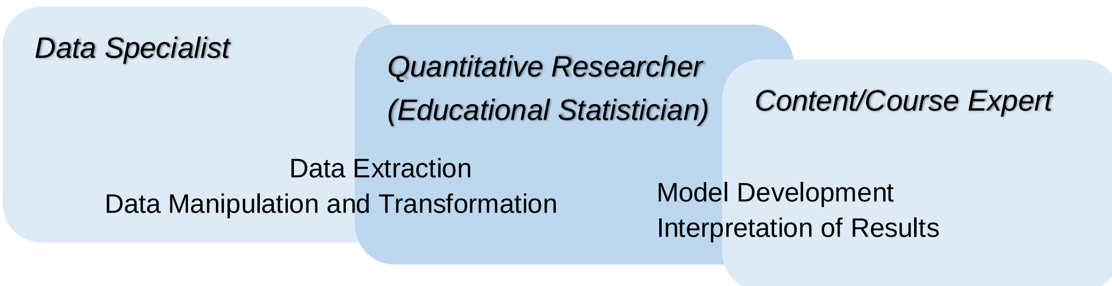
Analytic Approach	Descriptive analysis explored patterns of enrollment and passing rate, depending on student information variables, in particular locale codes. Then logistic regression examined the association between student information variables, in particular locale categories, and course completion status.
Implication	Although there is no common scenario on student success that spans across all virtual schools, some similarities were found: for example, lower performance related to the city locale. Both aspects of study findings (i.e., diversity and commonality) enhanced our understanding about learners in virtual courses by depicting how virtual schools serve students in each locale.
Study Case 5	**Lin, Kwon, and Zhang (under review)**
Reference	Lin, C.-H., & Kwon, J. B., & Zhang, Y. (under review). The effect of class size in online K-12 courses. Manuscript submitted to a peer-reviewed journal.
Study Site Data Source	This study used a school-wide 2013-14 dataset generated at a state virtual school in the Midwestern U.S.
Variables	• Student information: Gender, grade level, and reasons for enrollments • Focus variable: Class size (the number of students per session) • Outcome: Final scores in the course
Analytic Approach	Fractional polynomial analysis with multilevel modeling was used to find the optimal model explaining the association between class size and students' final grades.
Implication	Overall, increasing a class's size was positively associated with students' learning outcomes until such size reached around 45, after which it had a negative effect.
Study Case 6	**Lowes and Lin (2017)**
Reference	Lowes. S. & Lin, P. (2017). Student pathways through online Algebra 1 courses. Lansing, MI: Michigan Virtual University. Retrieved from http://media.mivu.org/institute/pdf/algebrapath.pdf
Study Site Data Source	Michigan Virtual School® (*MVS*) Algebra 1A courses during fall semesters of 2014 and 2015 academic year
Variables	• Course behavior: Week-by-week earned scores (from gradebook data), the number of weeks behind in comparison with pacing guide standards, and the time devoted to course components (from timestamped data) • Outcome: Course completion status (Fail/Pass) and the final score
Analytic Approach	Visual analysis of pacing patterns (heat maps), sequential analysis of access to course components (e.g., lessons, assessments, etc.), and cluster analysis and survival analysis to explore associations between pacing characteristics and learning outcomes
Implication	This analytic exploration informs how the students paced themselves against the course pacing guide, how they moved from one course component to another, and where in the course they encountered difficulties.

Study Case 7	Kwon (2017a) Kwon (2017b) Kwon (2017c)
Reference	Kwon, J. B. (2017a). Credit recovery learning profile from time-series clustering analysis of attempted scores. Lansing, MI: Michigan Virtual University. Retrieved from http://media.mivu.org/institute/pdf/creditrec2.pdf Kwon, J. B. (2017b). Exploring patterns of time investment using time-series clustering analysis. Lansing, MI: Michigan Virtual University. Retrieved from https://mvlri.org/research/publications/exploring-patterns-oftime-investment-in-courses/ Kwon, J. B. (2017c). Investigating course engagement patterns in mathematics and non-mathematics courses. Lansing, MI: Michigan Virtual University. Retrieved from https://mvlri.org/research/publications/courseengagement-patterns-in-mathematics-and-non-mathematics-courses/
Study Site Data Source	This series of studies used gradebook and timestamped data from the *MVS* LMS for particular courses (e.g., Algebra 2 fall semester).
Variables	• Time series variable: Week-by-week records of students' attempted scores, and week-by-week minutes recorded in the LMS • Student information: Enrollment reasons, in particular credit recovery • Outcome: Week-by-week earned scores and final grades
Analytic Approach	Time series clustering analysis was used.
Implication	Time series analysis is used to identify patterns among multiple attributes that might lead to a student's success or failure. The clustering technique generates meaningful subgroups based on the similarity of time series patterns. Unique characteristics of individual subgroups and their relationships to learning outcomes inform us what types of engagement patterns throughout the semester are more likely to relate to success or failure in the course. For instance, the largest group were the consistent and persistent coursework group from the weekly-attempted-score data and the final spike group from the weekly-time-spent data.

Closing Remarks

Learning analytics may be implemented in two ways, generally speaking. The first one is focused on stakeholders such as researchers, administrators, and policy makers, who seek insights into evidence-based practices and who undertake system-wide research or evaluation. In this vein, analytics highlights ***collaborations*** between various experts and specialists in order to make it reliable, valid, and rigorous. Figure 1 depicts the collaborative relationship among three representative types of experts.

Figure 1. Collaborative Relationship in Learning Analytics



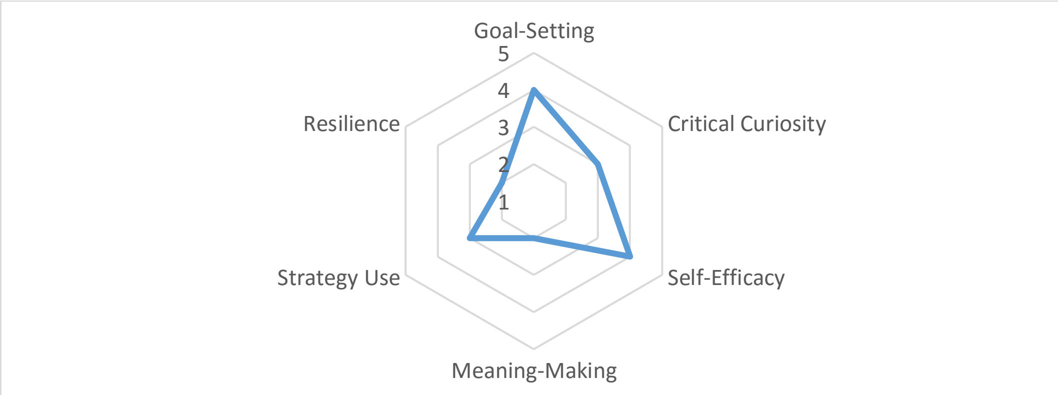
Data specialists can contribute knowledge about databases in collaboration with quantitative researchers in order to pull out necessary data. Data specialists' expertise is also important in terms of the effectiveness of analytic projects. For instance, the data of duration of online sessions can be obtained by transforming the raw data of timestamps by using Microsoft Excel or other statistical software. However, data in the appropriate format can be exported directly from the database at the data-extraction tools' level. Course designers, instructors, or online learning experts can contribute their expertise when the research questions are formulated, when key variables are selected for the model, and finally, when modeling results are interpreted in order to make constructive suggestions to stakeholders.

The next aspect of analytics infrastructure aims at generating useful and quality information to influence specific learning and instructional practices in a timely manner. This use of learning analytics emphasizes ***communication*** among stakeholders such as students, parents/guardians, instructors, and/or academic mentors; thus, making analytics easier to comprehend is critical. For instance, resultant information from analytics on students' perceptions of motivational constructs can be summarized graphically, as shown in the first example of Figure 2, and reported to students and educators whenever it is deemed necessary and useful. Students and educators reflect on resultant information from learning analytics, discuss individual strengths and weaknesses to be successful learners, and, in turn, shape practices of learning and instruction.

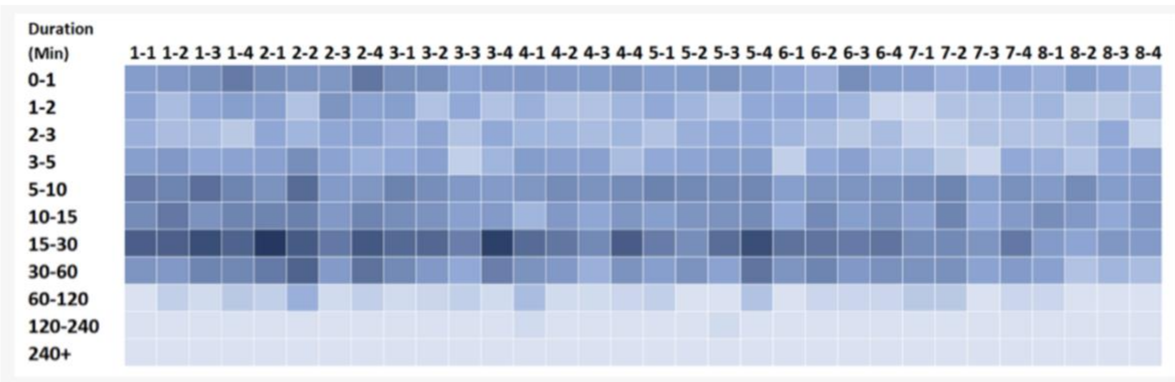
The heat map in the second example of Figure 2 consists of lesson units on the horizontal axis, ranges of time spent in particular course contents (i.e., lesson unit) on the vertical axis, and color-coded data entries for the number of students who showed particular time durations for each of the lesson units (i.e., the darker the color, the more students). It provides data to academic staff, such as instructors and course designers, on student engagement levels and patterns in a consolidated view, which, in turn, enables them to improve their ability to grasp information that brings actionable insights into the course contents and instructional practices in virtual classrooms.

Figure 2. Visualization Examples for Communications

Example 1: Coaching Conversation with Student Motivation and Disposition Profile Plot



Example2: Heat Map of Session Duration Engagement by Lesson [5]



Learning Analytics in Practice

In this section of the report, two programs from the Wisconsin Digital Learning Collaborative – Wisconsin Virtual School and Appleton eSchool – share the variety of ways in which they use data to inform teaching and learning processes in their programs.

[5] https://mvlri.org/blog/understanding-engagement-k-12-online-courses-part-one/

Wisconsin Virtual School

By Dawn Nordine and Michele Nickels

Wisconsin Virtual School (WVS) is a state-level virtual school that partners with schools and school districts across the state of Wisconsin. For this reason, the students are the local district's. The teachers may be local district teachers or WVS will provide highly qualified teacher consultants.

WVS uses learning analytics in a variety of ways. One of the most frequent approaches is looking at student data to support local mentors (also known as a local education guide or LEG) who will be reviewing student activity, pacing charts, and progress. They also provide coaching for the LEG, who will concentrate on the granular level of student data. The teachers at WVS have also been coached about how best to interpret the system data to help their students. WVS looks at the bigger picture completion rates of their students. Additionally, backend data provides an overview of teacher involvement in the course, including their response rate for grading and how many students they have that are behind pace or failing.

WVS also invites external researchers to conduct studies on the work that they are doing. Recently, they were involved in the Midwest Regional Education Laboratory's (REL) work on virtual learning. During this collaborative effort, researchers looked at WVS's student orientation course[6] to see its effect on student success rates. In addition to the orientation study, the REL also explored student engagement[7] with content. In addition, there was a report on teacher professional learning[8,9,10,11] that looked at what background teachers had in teaching virtually and what training they still needed. WVS is planning a follow up to that report that will help them understand where they were, where they are now, and where they want to go with regard to professional learning needs of their instructional staff. They also survey their LEGs to understand their needs and level of satisfaction with WVS. The support for the LEGs specifically for learning analytics comes in the form of Lunch and Learns (webinars) or through just-in-time support.

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6 https://drive.google.com/file/d/0B1dUYVSka22PVS1xZ2x3bGhRRUk/view
7 http://www.virtuallearningalliance.org/research-and-reports/
8 https://ies.ed.gov/ncee/edlabs/projects/project.asp?projectID=1463
9 http://blogs.edweek.org/edweek/urban_education_reform/2017/11/learning_about_training_needs_of_online_teachers.html
10 http://blogs.edweek.org/edweek/urban_education_reform/2017/11/what_do_online_teachers_need_to_succeed.html
11 http://www.virtuallearningalliance.org/blog/

Currently, WVS wants to look at teacher completion rates course-by-course and combine that with teacher professional learning data, as well as the engagement work, to fully understand what is happening in teaching and learning at WVS. With this data, they approach school districts to have conversations about the needs of the students and the various education stakeholders with whom they are involved. This data provides them a platform from which to understand the needs of their stakeholders and inform their approach to the services they provide.

They recently incorporated an additional means to communicate student data directly with parents/guardians. The Observer Account allows parents/guardians to access the student information system and LMS to see their child's progress and what they need to do in order to advance in their learning. This allows them to be an active part of the support team for their child. Teachers work hard to help the parent/guardian navigate the information provided in the systems. Rolling out this feature to them, WVS included a screencast and screen shots of what the parents/guardians can do in the system. Some districts also ask WVS to join their Student Orientation or Open House nights to help orient everyone to virtual schooling. The WVS mindset is "What more tools can we give parents to be informed?"

WVS is also working with learning analytics in their collaboration with the National Repository of Online Courses (NROC) Network EdReady, the college and career math readiness program. They receive extensive amounts of data from this project, and eventually, longitudinally, they might be able to track student progress based on the help that they received from this program. There is also a way to combine this effort with career pathways that students can take based on their individual interests. For instance, one WVS student was enrolled in Forestry and Natural Resources. Because there is a forestry and natural resources math readiness pathway, he was able to embark on that path based on his personal interests. Currently, there are no schools providing credit for an EdReady math or career prep course.

One of the main challenges faced by WVS is that they are a staff of six and do not have a dedicated person to look at all of the data they have access to. Thus, the review of the data becomes a team effort. When needed, they run their own reports to try to understand trends. They also are looking at the importance of interoperability of their services, especially the tutoring service they partner with, which speaks to the backend of their own LMS so they can see whether or not a student is struggling and/or taking advantage of the tutoring service.

The most important idea out of the WVS approach to learning analytics is that if we look at our own data, we look at it through our own lens. We have a great staff who each come to the table with a different perspective, so it helps to have all of us share our interpretation of the data. What we like to do, if possible, is have an external researcher come in and let us know if they're seeing the same thing and whether or not we're interpreting it correctly. Because it's easy for us to say, "We think it is this way!" and we can find a piece of data to support that, we think having an objective party involved is important for this process of learning analytics.

Appleton Area School District

By Erik Hanson

We are the Appleton eSchool, the online charter school of the Appleton Area School District. We started back in 2001-2002, and this is my 10th year running Appleton eSchool. A majority of our students are part-time, taking one or two classes with us as part of their online learning experience in our school district. We serve maybe 20 to 30 students a year in a full-time capacity. One of our core beliefs is that we don't recommend they take all their classes online; therefore, we're really working on the blended experience.

In terms of learning analytics, we use data to help keep track of course completions and our progress toward our goal of 80-90% of our graduates taking an online course. For this reason, we've had to structure our systems to allow us to use data to help us follow the paths of freshmen, sophomores, juniors, and seniors through our system to see our progress toward reaching that goal. We've had to figure out ways to measure, ways to get the data, and ways to measure it well also. In addition, we've just started using data to look at the demographics of who we're serving. We've asked questions such as, *does our population of students taking online courses match our populations across the district? Is our student population just one subgroup, or is it many groups of kids taking courses with us?* That's been an eye-opening experience in using data.

We're also starting to figure out how to do better CSV file uploads into systems using data for rostering and reporting. With this work, we find our team at Appleton eSchool and the Wisconsin eSchool Network becoming more involved and connected to IMS Global.[12] Their one-roster standards help us get better at allowing data and demographics to flow back and forth without complications, so we're working on getting access to data, transferring data, and understanding how to share data properly.

We also implemented the post-high school initiative this year, which is a badge or credential that goes on student high school transcript. The badge is triggered when students are successful in our online courses, scoring a B or better without plagiarizing. We wanted to recognize academic honesty and promote that and say, "Hey, we value the fact that you're doing your own work, and that's important." Our secretary enters the student data once it's reported by a teacher, so the badge indication is generated in our student information system. Right now it is a text only field, but we are working to make that a graphic or image in the near future by working with our SIS

[12] https://www.imsglobal.org/

and IMS Global. Last year was the first year we were approved to put the “Online Course Ready for Post High School” badge on the students’ transcripts to communicate to students’ colleges and employers that students have these particular skills and core attributes for online learning. This is a way for us to communicate that online learning is part of what students do in the Appleton Area School District.

While there are plenty of positives for learning analytics, the biggest challenge for Appleton eSchool is clean data. We have a lot of data; but if it's not clean, we have to factor in the time to clean it to see if we can actually do something with it securely and safely. Because of this, we spend time critically thinking about how we're going to get quality data. There are many people in the field talking about the need to “Amazon-ize predictive behaviors and learning,” but those same people typically don’t understand what goes into making that happen. I was just at the IMS Global quarterly meeting in Seattle, Washington, last week, and the CIO of University of California-San Diego, was speaking. He basically looked at everybody and said, "I know districts and people are asking for ridiculous AI type customizations to software right now, and it's going to take decades and decades of the community's work to pull that off, so just settle down. Relax." It’s so true, and it was actually really good to hear because it's so easy for people, I'm sure I've been guilty at times, to say, "Oh yeah. We'll just figure out predictive things and let the algorithm tell us what might happen." To understand the complexity of what you're talking about is insane, especially since data does not transfer well in the education space at all between LMSs, SISs, and state systems. That planning wasn't put in place before all this data was created. Now Ed-Fi, IMS Global, and other initiatives are starting to put this into perspective. Standardizing interoperability is a huge part of it, and, to me, that's the building block of being able to do what people are hoping to do with data someday.

The interesting thing is that everyone acts as if they have it all figured out; but when you really get them to dig deeper into what they’re using, they typically relay that they’re not satisfied with the way a tool works. In other words, I don’t think it's as easy as everyone makes it out to be. You have to be careful when you're using data to make your decisions, because, as we all know, people can make data look however they want to make it look, so I think it comes back to your vision, core beliefs, how you do business as a program, and what problem you want to solve. So we ask questions such as, *What do we believe? What do I believe? What does our team believe? What are we trying to accomplish? What problems are we solving?* I think you have to start there. I don't know if I would have truly understood the value when I first started using data in learning unless I struggled with what we struggle with within the current system.

Ultimately, I need to experience going through this process of understanding the challenges and the struggles and the pain a little bit, so I appreciate and understand the need for interpretable data systems that can communicate between each other. I'm highly optimistic for the future, especially with the work that IMS Global is doing and how important a role we all play in informing their processes, because the system will not change until we ask it to, and it won't change until there's enough of us that ask it to. Really it's about the people and the organizations.

Considering the possibilities of what data can help us continue to grow, we have to remember that data doesn't do things for us. We have to remember that we are the ones that take action, and we are the ones that make decisions, and we are the ones that have to put kids and learning first. We have to continue to keep that as our main focus and understand that what we believe is all tied together. Data is just another tool. It's another source of information to help us make decisions – and good decisions at that, hopefully. Having come a long way from where we've been, I have a better understanding of how much work this is and that it's not just a one-person job. It's going to take a community effort, a collaborative effort, to go the direction we're hoping to go, and to me, that's exciting, too.

Resources and Contact Information

The programs involved in this report also shared their contact information in case anyone would like to be in touch to learn more:

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- Grantsburg School District
- Green Bay Area Public School District
- School District of Janesville
- Kenosha Unified School District
- Kiel Area School District
- Kimberly Area School District
- Madison Metropolitan School District
- Middleton-Cross Plains Area School District
- Oshkosh Area School District
- Racine Unified School District
- Sheboygan Area School District
- Wisconsin Virtual School (CESA 9)

Affiliate Partners

- Cameron School District
- Chetek School District
- DeForest Area School District
- Franklin Public School District
- Kewaskum School District
- School District of LaCrosse
- Medford School District (Rural Virtual Academy)
- School District of Nekoosa
- River Valley School District
- School District of Superior
- Stevens Point Area School District
- Triton Network
- Watertown Unified School District
- Waunakee Community School District

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